Driving Anomaly Detection with Conditional GAN using Physiological Data & CAN-Bus Data

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Motivation

Goal: Categorization of driving data for future driver assistance systems

1. Known-knowns

Easy and usual situations:
(Situations that we know and know how to handle)
- Freeway driving

2. known-unknowns

Very difficult situations:
(Situations that we know are difficult, but not know how to handle it)
- complex intersection

3. Unknown-knowns

Beyond-control situations:
(Situations that we give-up to handle)
- Flying vehicle
- Reckless ped. behaviors

4. Unknown-unknowns

Solution: ????

Unexpected situations:
?????

5. Driver errors

First target → Detection of "anomaly" situations 2-5

Motivation

- **Examples include:**

  Driver errors:
  - Lack of awareness of objects, pedestrians, or vehicles

  Anomaly surrounding situations:
  - Hazard actions from other vehicles
  - Unexpected changes that leads to hazard scenarios

- **Our approach: (←→ Supervised approach, Look-outside approach)**
  - Unsupervised methods without pre-set patterns
    - Patterns of abnormal driving scenarios are difficult to determine
    - To discover unknown abnormal scenarios
  - Detect anomalies from driver reaction

    ← Driver should have reacted to anomalies (Driving is "interaction"!)

On-road pedestrian

Hazard action

Multimodal Signals – From our Previous Work

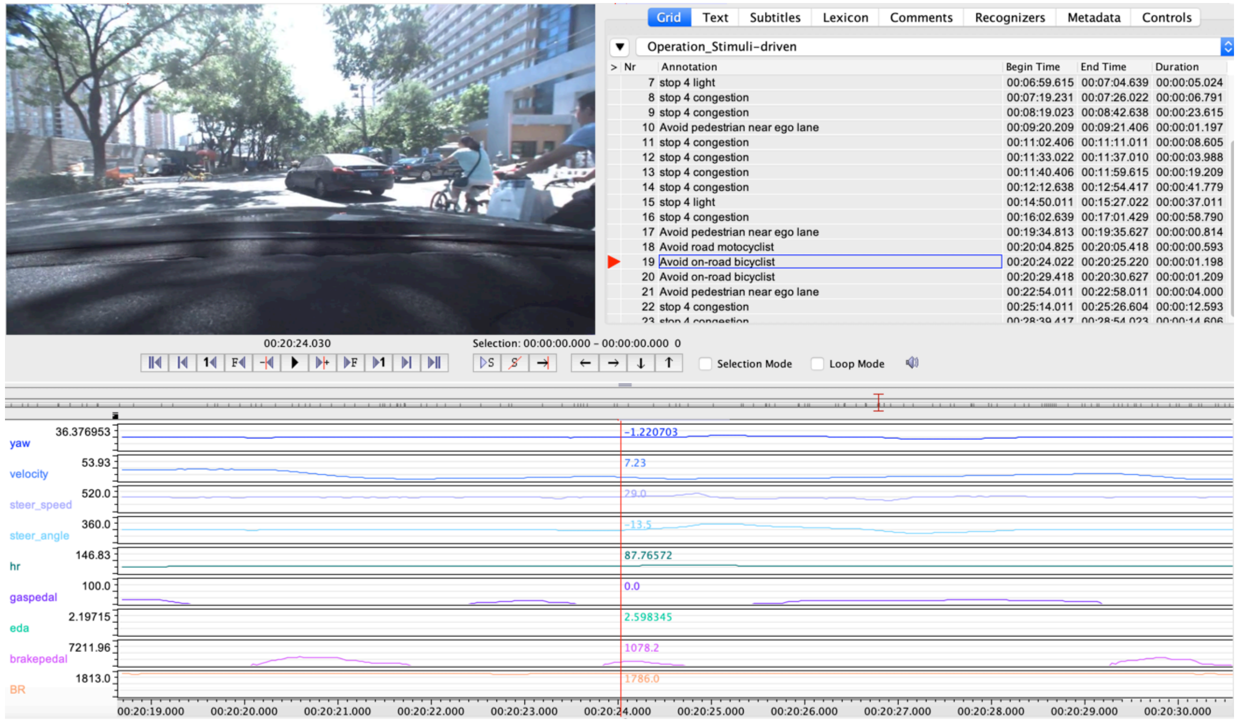
- **Relationship between driving maneuvers and drivers' physiological signals [Qiu et al., 2019]**
  - Heart rate (HR), Breath rate (BR), and electrodermal activity (EDA) can be used to discriminate different driving maneuvers
  - Physiological signals respond to other events (e.g., driver stress, surprise)
- **Physiological signals are useful for driving maneuver classification when combined with features extracted from CAN-bus data [Li et al., 2016]**

In this work, we tackle anomaly detection using
- CAN-bus data
- Physiological signals (HR, BR, EDA)
- (NO images/videos)

1. Motivation
2. Driving Anomaly Dataset (DAD dataset)
3. Proposed Model
4. Experimental Evaluation
5. Conclusions

Driving Anomaly Dataset (DAD)

- **250 hours of naturalistic driving recordings**
  - Single driver
  - 48 hours used in this study
- **Collected in a city in Asia**
- **Driving events are manually annotated based on forward-facing in-vehicle camera**



Driving Anomaly Dataset (DAD)

- **Annotations** **[Ramanishka et al. 2018]**
  - A four-layer representation
    - Goal-driven actions
    - Stimulus-driven actions
    - Cause/Attention
  - Traffic rule violations

	Annotations
Goal-driven Action	Intersection passing; Left turn; Right turn; Left lance change; Right lance change; Crosswalk passing; U-turn; Left lane branch; Right lane branch; Merge
Stimulus-driven Action	Stop; Deviate
Cause	Sign; Congestion; Traffic light; Pedestrian; Parked car
Attention	Crossing vehicle; Crossing pedestrian; Red light; Cut-in; Sign; On-road bicyclist; Parked vehicle; Merging vehicle; Yellow light; Road work; Pedestrian near ego lane

- **Signal data collected**
  - Drivers' physiological data
    - Heart Rate (HR)
    - Breath Rate (BR)
    - Skin conductance (EDA)
  - Vehicle controller area network (CAN)-bus data
    - Speed
    - Yaw
    - Steer speed
    - Steer angle
    - Pedal pressure
    - Pedal angle

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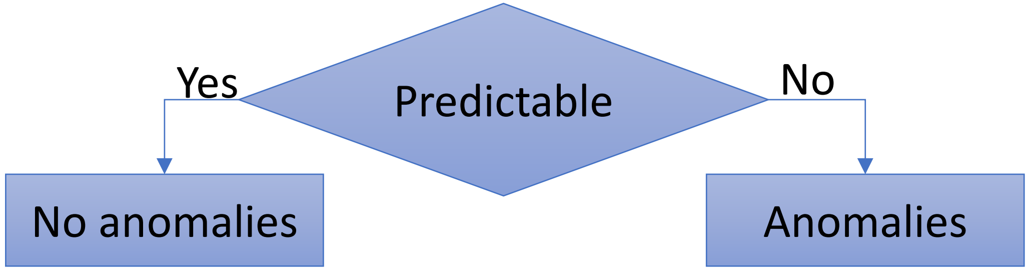
Big Picture Idea

Previous frames

Future frames

- Can we forecast the "signals" in upcoming recordings based on previous frames?

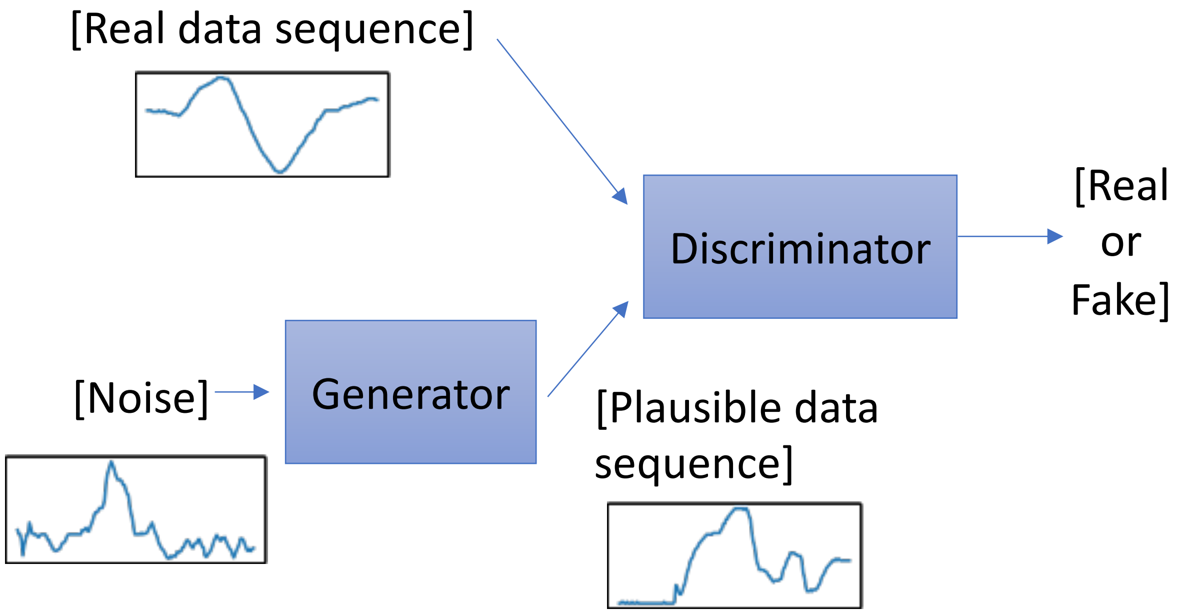
Predictable or Not?



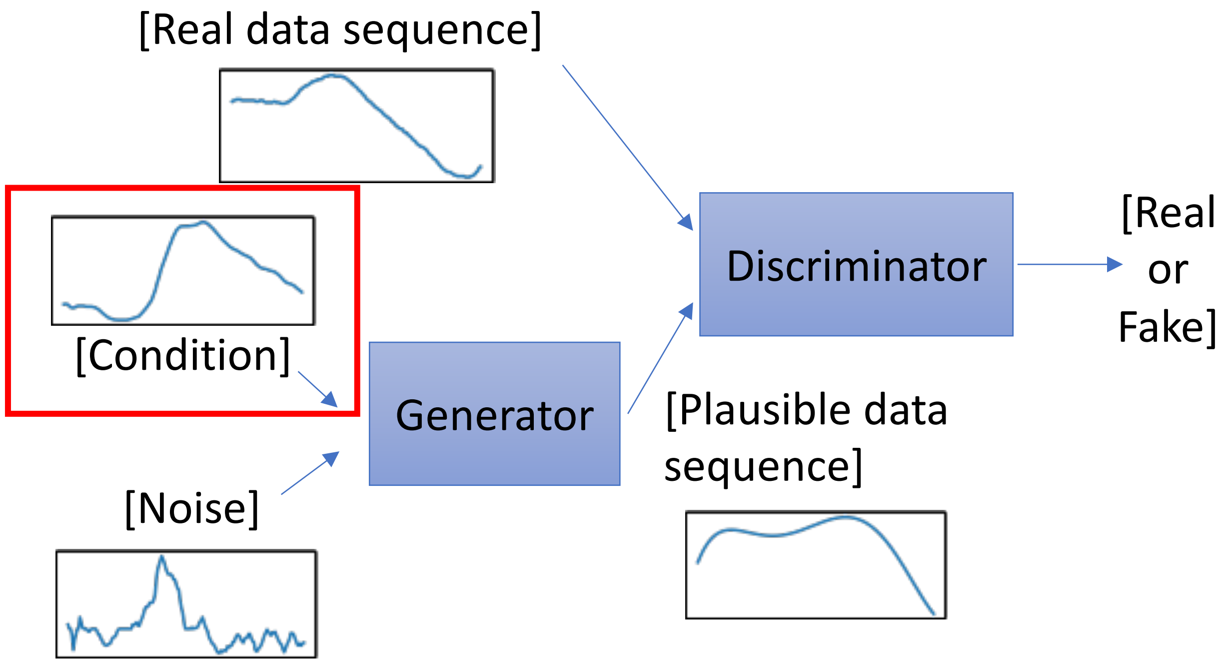
Next step: How to define "predictability"
→ We actually generate predicted signal and compare with real signal

Generation and Comparison using GAN

- **Generative Adversarial Network (GAN)**
  - Generate plausible data from random noise



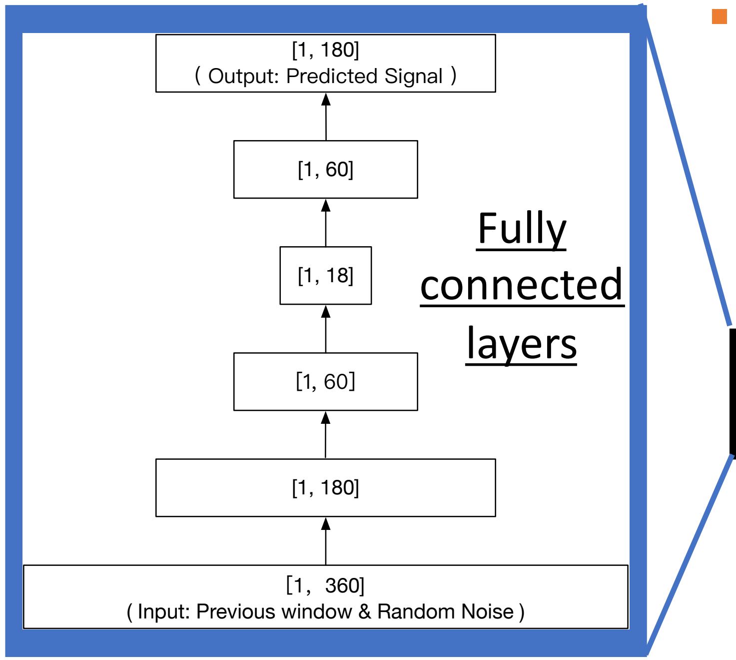
- **Conditional GAN (cGAN)**
  - Input: Condition & Random noise
  - Generate data constrained by *condition*

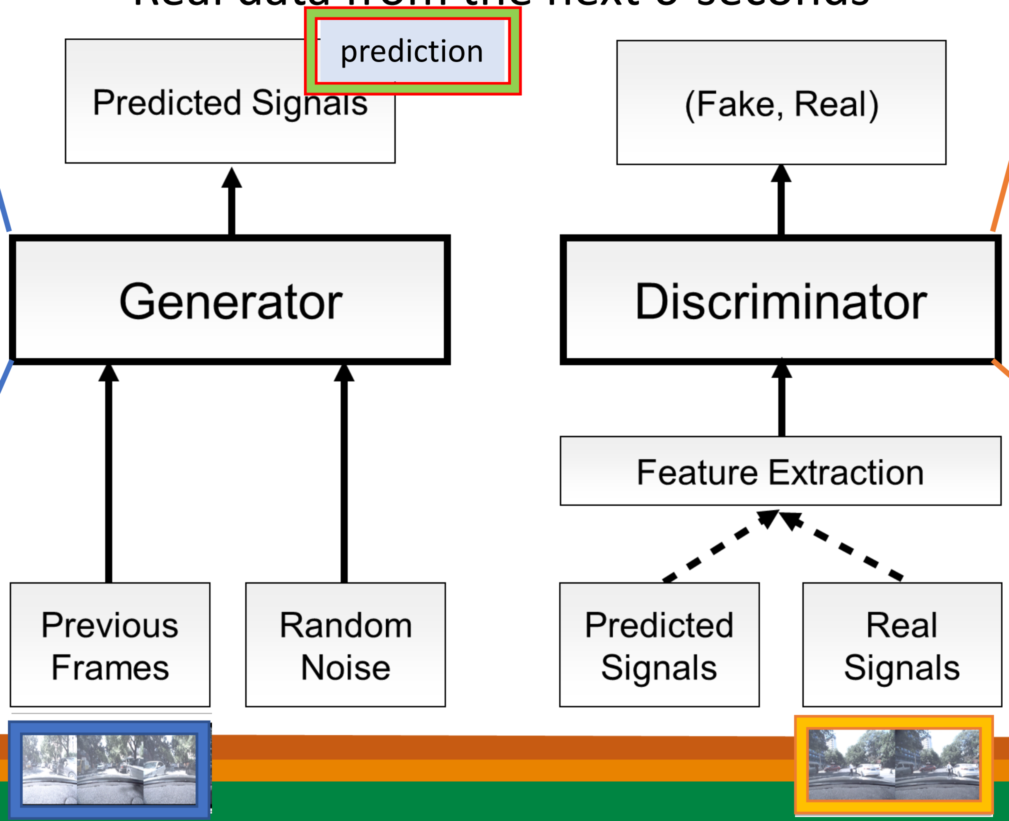


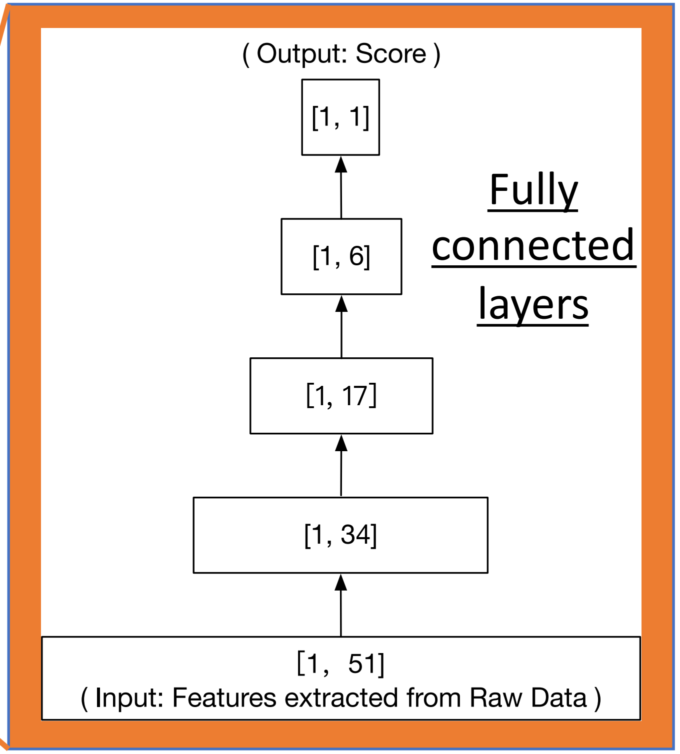
Proposed Model for Anomaly Detection

- **Training Process**

- **Condition of CGAN**
  - Real data from previous 6-seconds
- **Random noise:**
  - Random noise, totally unrelated to real data
- **Real signals:**
  - Real data from the next 6-seconds

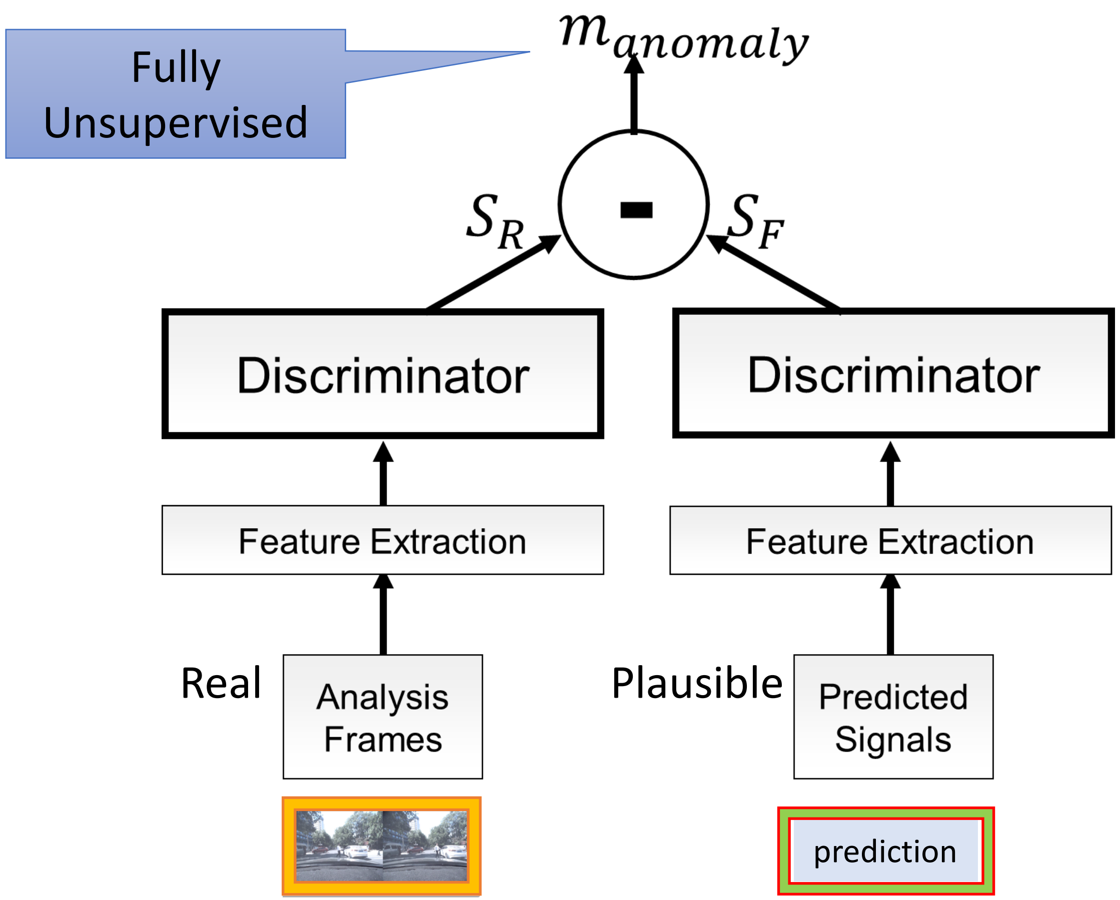






Proposed Model Structure

- **Testing Process**



- **Analysis Frames:**
  - Real data from next 6-seconds
- **Predicted Signals:**
  - Prediction from our conditional GAN model

- **Feature Extraction:**
  - Time domain (CAN-Bus & Physiological):
    - Mean, Standard Deviation (Std), Max, Min
  - Frequency domain:
    - Energy covering the following 5 bands: [0-0.04 Hz], [0.04-0.15 Hz], [0.15-0.5 Hz], [0.5-4 Hz], [4-20 Hz]

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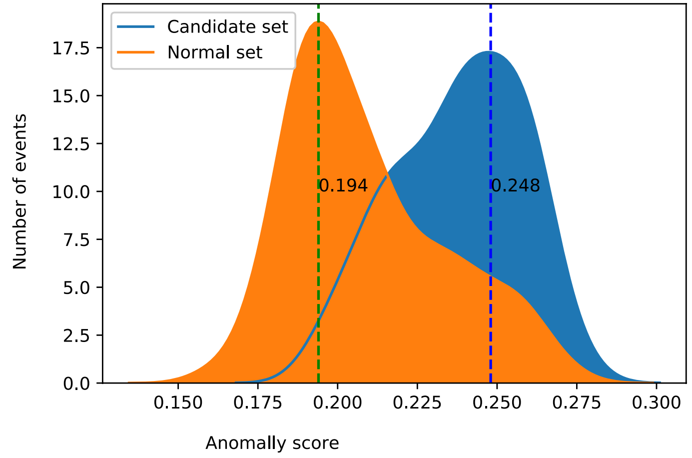
Evaluation – Anomaly Score Distribution

- **Split the driving segments into 3 sets of segments according to the annotations**
  - Candidate set
    (Expected to be more anomalous)
    - Avoid on-road pedestrian
    - Avoid bicyclist near ego-lane
    - Avoid parked vehicle
    - Traffic rule violation
  - Maneuver set (known difficulties)
    - Intersection passing
    - Right turn & Left turn
    - Left lane change & Right lane change, etc.
  - Normal set
    - Segments with no event annotation

- **Distribution of anomaly scores $m_{anomaly}$ for segments from the normal set and the candidate set**



- **Annotations Overlapping with Segments**

Events	Normal	Candidate	Maneuver
Top 100	16	9	75
Random 100	59	3	38

Our approach can detect anomalies

Examples of Events Identified as Anomalous

- **Example segments with high anomaly score**

Avoid on-road pedestrian

Avoid on-road bicyclist

Left lane change
(Another vehicle cuts in
at a T-intersection)

Evaluation - Perceptual Evaluation

- **MTurk GUI**

Watch the videos first. Then answer the questions about your feelings. (Click to expand)

Video

Q1: How risky is the driving maneuver in the video

- ○ safe maneuver
- ○ slightly risky
- ● risky maneuver
- ○ very risky maneuver

Q2: How often do you see similar driving scene on the road

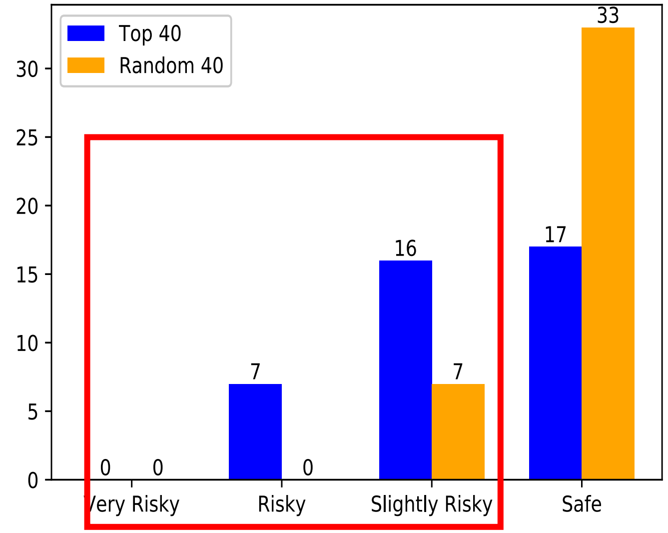
- ○ never
- ● rarely
- ○ sometimes
- ○ quite often
- ○ regularly

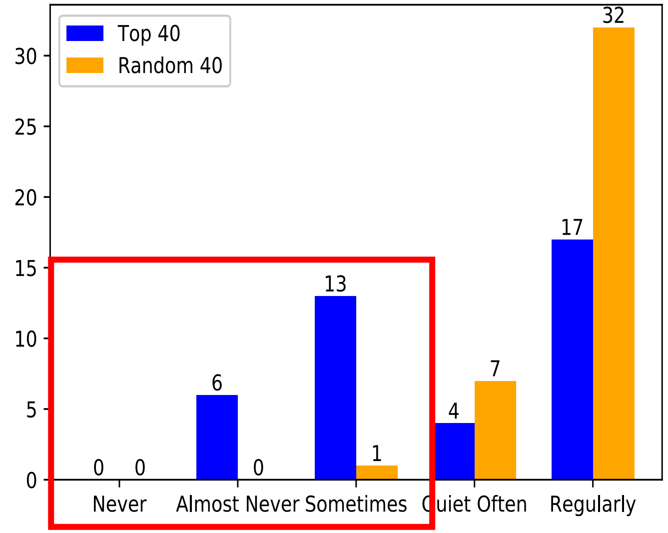
Evaluation - Perceptual Evaluation

- **Perceptual Evaluation Results on the selected Top-40 and Random-40 segments**

  2 questions, 4 evaluators (for Top-40 + Random-40 videos)

  - How risky is the driving maneuver in the video?
  - How often do you see similar driving scene on the road?

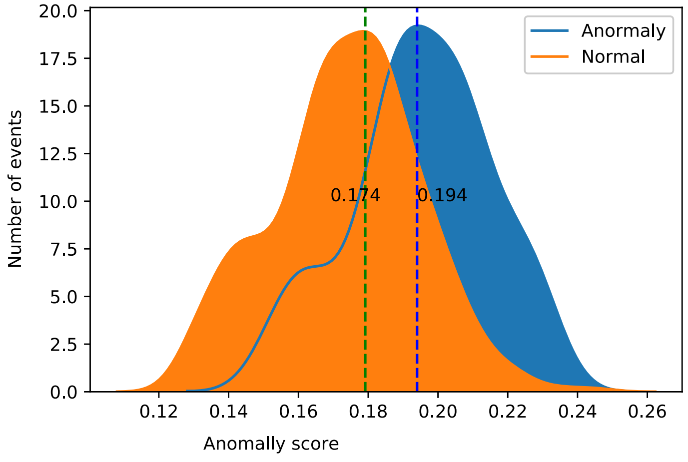




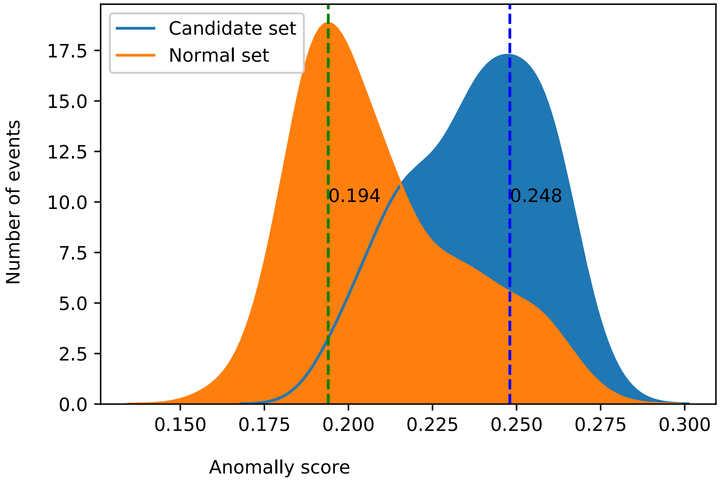
Proposed unsupervised approach is able to identify anomaly events

Evaluation – Effect of Physiology Data

- **Role of Physiological Data**
  - Can we perform this task with only CAN-Bus data?
  - → We reimplemented the network using <u>only CAN-Bus features</u>
    - Evaluate whether physiological data is really for anomaly driving detection
- **Result:**



Only CAN-Bus data



CAN-Bus + Physiological data

Physiological data increase separation between normal and candidate sets

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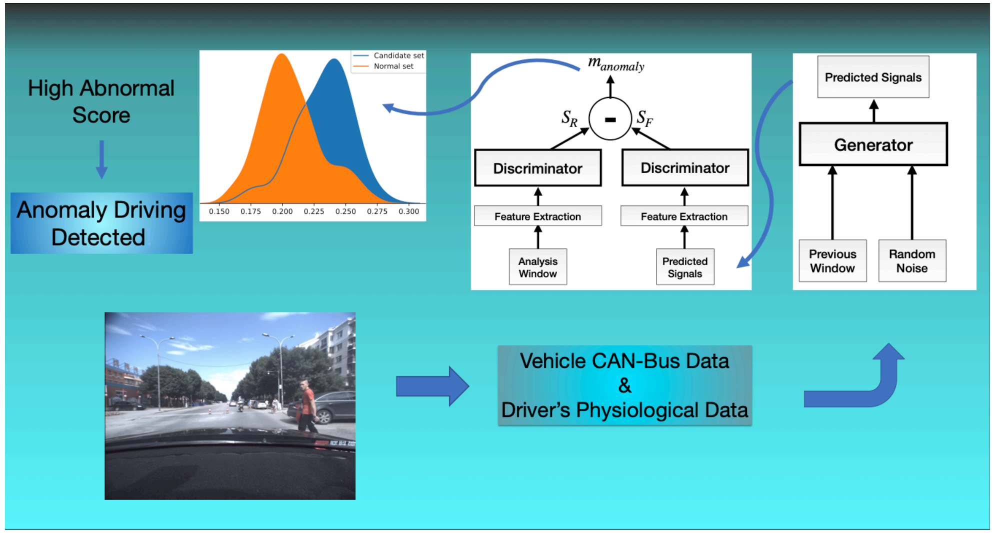
Conclusions

- **Multimodal unsupervised driving anomaly detection method using Conditional GAN**
  - Based on predictability of physiological signals and CAN-Bus data signals
  - Condition the models by previous frames

  → Detecting driving anomalies that involve changes in the driver's mental state or unexpected driving maneuvers
  - A method that does not depend on predefined rules set with either ad-hoc thresholds or supervised methods



Limitations and Future Work

- **Limitations**
  - Model is able to identify anomalies only when the driver reacts to them
  - Need for normalization strategies for physiological data to compensate drivers' variability
    - Experienced versus novice driver
    - Aggressive versus calm driver
- **Future Work**
  - Incorporate other information
    - e.g., Object detection results
  - Improve the implementation of the proposed conditional GAN model
    - Recurrent neural networks (RNNs)
    - Convolutional neural networks (CNNs)

Any Questions?